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TRADEOFF ANALYSIS TOOLS FOR HYBRID NDE-SHM LIFE MANAGEMENT STRATEGIES (PREPRINT)

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14. ABSTRACT
Hybrid life management strategies for new and aging aircraft have been proposed that combine traditional non-destructive evaluation (NDE) methods and recently developed structural health monitoring (SHM) technologies. In recent times, a usual aim for managing the life of aircraft components that are critical or that are subject to fatigue or corrosion damage is to attempt development of in situ damage detection systems that can indicate when more detailed inspection is necessary. This creates a need for decisions about the type and settings of sensors and signal processing algorithms for the health monitoring system, and system type, settings, and scheduling for NDE. How well these systems are matched will have great influence on overall maintenance cost, aircraft availability and system reliability. In this presentation, a software package is presented for integrating NDE and SHM design with product life management models.

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Tradeoff Analysis Tools For Hybrid NDE-SHM Life Management Strategies

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Abstract

Hybrid life management strategies for new and aging aircraft have been proposed that combine traditional non-destructive evaluation (NDE) methods and recently developed structural health monitoring (SHM) technologies. In recent times, a usual aim for managing the life of aircraft components that are critical or that are subject to fatigue or corrosion damage is to attempt development of in-situ damage detection systems that can indicate when more detailed inspection is necessary. This creates a need for decisions about the type and settings of sensors and signal processing algorithms for the health monitoring system, and system type, settings, and scheduling for NDE. How well these systems are matched will have great influence on overall maintenance cost, aircraft availability and system reliability. In this presentation, a software package is presented for integrating NDE and SHM design with product life management models. Based on probabilistic models of fatigue crack growth, NDE detection capability, repair, probability of failure, and cost, the demonstration cases show the ability of the software tool to assess the effects that changes in SHM parameters, NDE parameters, and maintenance scheduling can have on time-dependent reliability and economic service life objectives. Furthermore, the method and software can facilitate design tradeoff assessment and optimization for goals such as cost, reliability, and system availability. Example design cases include (1) analysis of near- and long-term costs and benefits of SHM applications, considering time-dependent sensor reliability, to provide insight into the potential opportunities and challenges of SHM applications and (2) assessment of maintenance programs that combine NDE and SHM systems. Several example cases are presented which demonstrate that the software enables analysis of tradeoffs among cost and reliability in aircraft component life management strategies based on NDE and SHM.

I. Introduction

Most current U.S. Department of Defense acquisition and sustainment programs place a strong emphasis on affordability as a priority goal. The need for cost awareness and reduction has been widely publicized within all government organizations. Cost reduction is a main focus in all manufacturing technology programs for both military and industrial sectors. In 1999, the U.S. Air Force, the U.S. Navy, and the Defense Logistics Agency commissioned a group of renowned military and industrial leaders in defense manufacturing to “identify a framework for defense manufacturing in 2010 and to recommend strategies for attaining the capabilities that will be needed” [1]. That study clearly identified that “the principal criterion for prioritizing manufacturing capabilities should be potential cost savings.” On the subject of computer aided design, the study stressed the need to make the most of simulation-based design environments by, among other means, promoting the development of models of defense products, manufacturing processes, and life-cycle cost performance, developing algorithms for design tradeoffs to optimize life-cycle costs, and developing enhanced and easily usable parametric models that facilitate design trade-offs at the conceptual design stage. The importance of controlling sustainment costs is epitomized by

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the fact that many old U.S. Air Force aircraft (20 to 35+ years) are expected to remain in service another 25 years, and they usually encounter aging problems such as fatigue cracking, stress corrosion cracking, corrosion, and wear [2]. Cooke et al show that the annual costs of maintenance due to corrosion of weapon systems and equipment within the Air Force is already many hundreds of millions of dollars, and that these costs are steadily increasing [3]. Given the importance of inspection and the impact of defect identification and maintenance on service life, the National Research Council Committee on Aging of U.S. Air Force Aircraft recommended in 1997, among other tasks, the improvement of economic service life estimation methods, and the application of computational methods and simulations in the development and evaluation of inspection techniques [1]. Large portions of the budgets of many military and commercial organizations are devoted to the maintenance of existing systems. Effective and cost-efficient evaluation of quality and life expectancy of new or existing systems or components depends on the accuracy and cost of the evaluation method.

The U.S. Department of Defense Condition-Based Maintenance (CBM) and CBM Plus (CBM+) initiatives aim to improve maintenance agility and responsiveness, increase operational availability, and reduce lifecycle total ownership costs [4]. CBM is defined as “a set of maintenance processes and capabilities derived from real-time assessment of weapon system condition obtained from embedded sensors and/or external tests and measurements using portable equipment.” The goal of CBM is to perform maintenance only upon evidence of need. “CBM+ expands on these basic concepts, encompassing other technologies, processes, and procedures that enable improved maintenance and logistic practices throughout the life cycle of a system [5].” Nondestructive evaluation (NDE) and structural health monitoring (SHM), both independently or combined, provide capabilities that are necessary for the success of the CBM and CBM+ initiatives. NDE can help provide offline damage identification and tracking capabilities that are necessary for implementing maintenance based on system condition. SHM utilizes embedded sensing systems to generate real-time and offline information for maintenance decision support. Programs that implement CBM/CBM+ can utilize NDE and SHM in a complementary fashion.

Nondestructive evaluation methods play a major role at all stages of design, manufacturing, and service life; however, the benefits of effectively taking into account inspection knowledge in order to positively affect life-cycle figures of merit have not been fully realized, because current design tools do not address the impact that inspection decisions have on performance, life, and cost tradeoffs across multiple stages of the life cycle. Effectively addressing life-cycle affordability requires consideration of entire production sequences and product maintenance procedures, during all design phases, and in particular at the conceptual design stage, when most of the life-cycle cost is decided. Since NDE is used throughout manufacturing and service life stages, taking into consideration NDE information at early design stages can significantly improve affordability because all decisions on materials, component and assembly geometry, and manufacturing processes can be made while taking into account the need and ability to inspect at particular locations and intervals, as well as the cost of such inspections which also depend on the method chosen. This is true even for cases where the decision among existing applicable NDE methods is straightforward, but is more applicable when engineers face problems where a new material, design, or problem will require careful consideration of candidate inspection techniques, or possibly the design of a new inspection method. Thus, design tools are needed to optimize the inspection techniques for optimal fleet service life management. This paper presents the development of a software platform for aircraft economic service life management and presents example cases which demonstrate that the software enables analysis of tradeoffs among cost and reliability in aircraft component life management strategies based on NDE and SHM.

II. Background

A. NDI and Reliability

Nondestructive evaluation (NDE) consists of test methods used to examine the material integrity of an object or system of objects without impairing its future usefulness. It is used to detect and characterize anomalies in materials and structures in order to ensure their reliability and extend their service life. NDE includes visual, ultrasonic testing, eddy current testing, magnetic particle testing, fluorescent penetrant testing, radiography, infrared imaging, and thermography methods. NDE can be used for identifying discontinuities such as cracks, porosity, corrosion, and wall thinning, and is often applied at several stages of manufacturing processes, and during scheduled maintenance after products are in service. Over the years, NDE has become increasingly used in many stages of a product’s life cycle, and has contributed significantly to material process control, part fabrication, and economic service life management programs of industry and government.

The reliability of nondestructive evaluation techniques is critical for aircraft maintenance programs. Issues in nondestructive inspection discovered through probability of detection studies have generated an interest in determining the impact of inspection performance on total service life [6]. For inspection problems that include manual scanning, complex procedures, and low frequencies of finding critical flaws, there is a potential for some critical sites to not be inspected effectively due to the requirements of the inspection process, or there are inconsistent requirements for calling marginal defects [7]. Options for addressing NDE reliability issues associated with human factors include improved design of NDE equipment and procedures, consistent evaluation of NDE reliability through POD studies, and improved NDE process controls using quality calibration standards, increased inspector training and evaluation, and improved management oversight. Alternatively, the application of structural health monitoring (SHM) systems with in-situ sensors also has the potential to improve inspection reliability by eliminating problematic human factors. To properly assess the best methods to maintain acceptable inspection reliability and minimize total life cost, tools to evaluate NDE and SHM systems using probabilistic risk assessment with cost-benefits analysis are needed.

B. Structural Health Monitoring

The application of in-situ sensors for structural health monitoring has been proposed with significant research and development programs ongoing [8,9,10,11,12]. The primary benefit of structural health monitoring (SHM) concerns integration with prognostics, where the management of high value assets such as military aircraft is improved through the quantitative prediction of future operating capability and accurate determination of remaining life. Potential cost benefits for SHM include (1) reductions in labor cost and time for unnecessary nondestructive evaluation (NDE) inspections, (2) management of locations of limited accessibility to minimize costly teardowns, and (3) availability of robust indications of impending failure of the structure to trigger safe retirement. Improvements in availability of aircraft can also be addressed using SHM by limiting time in maintenance to only when absolutely necessary. In addition, SHM, when considered during the aircraft design phase, has the potential to provide engineers with the means to reduce structure weight by avoiding conservative designs, reduce the need for costly assessments of fatigue critical locations [8], and improve aircraft dynamic performance. Additional benefits may also be realized through the use of in-situ sensor data to indirectly measure wing conditions of interest such as excessive loading or icing conditions, and to support accident investigation, potentially leading to a safer fleet over the long-term.

Limited studies have been presented to date concerning the cost justification for SHM applications [9,10,11,12]. The costs associated with structural health monitoring systems can be categorized as development costs, implementation costs, and in-service costs. Development costs include any initial research and system development work for a particular application. Implementation costs are associated with the fixed initial cost for purchasing and installing the on-board SHM system and for performing validation studies to satisfy reliability requirements. Both development and implementation costs are expected to be much higher for SHM system with respect to those of NDE techniques, given the increasingly difficult system requirements concerning inspection and reliability. Lastly, in-service costs can include the additional cost of fuel due to added SHM system weight, data interpretation labor costs, SHM maintenance costs, and the cost of secondary inspection and unnecessary repair due to false calls or unnecessary calls when flaws are very small. While in-service costs of SHM systems are expected to be low in relation to those of NDE procedures, design-time consideration must be given to the possibility for such costs to be significant in order to minimize their impact on total life cycle cost.

Many challenges exist for the practical application of in-situ sensors for SHM. First, there is the significant challenge to quantify the damage state of a structure, distinguishing mission critical defects such as fatigue cracks, excessive corrosion, or delaminations from coherent noise features present in distributed sensor signals. For example, regular depot maintenance actions such as grindout of corrosion, replacement of select panels, and application of patches, will alter the dynamic characteristics of a structure, and the corresponding changes in sensor signals must be differentiated from the detection and characterization of critical defects. Likewise, time-driven variations in the structural contact conditions at joints and fastener sites or changes in the sealant properties will also impact the global dynamics of a structure. Many in-situ SHM approaches are also sensitive to changes in the dynamic, thermal, and mass loading of the structures, which can be considerable during flight or at different bases around the world. In addition, observability and sensor placement are critical considerations when attempting to evaluate the damage state on both global and local levels. Another significant issue is the degradation of the in- situ health monitoring system, where a variety of sub-systems such as the sensors, the bonds between sensors and structures, the wiring harnesses, the measurement hardware, and the power (battery) system have the potential to decay over time. Lastly, to transition SHM systems from research to application, a key step is ensuring the reliability of the system through validation studies. To address the high cost of validating NDE procedures, model-assisted probability of detection (MAPOD) approaches have been proposed and demonstrated [13]. Such methods will become even more valuable to in-situ SHM approaches where it is highly expensive and time consuming to conduct experimental studies that address all significant variables under in-service conditions.

To properly address these issues, a methodology incorporating cost benefit analysis with probabilistic risk assessment is proposed for evaluating the overall value of SHM systems. These design tradeoffs must be examined from an economic service life management perspective where reliability, availability, and total cost of aircraft sustainment processes are quantified. This effort builds upon prior work concerning the development of a strategy and software framework for integrating NDI design and product life management tools [14]. This model is based on prior work by Berens et al., who developed a software tool, PROF, for probabilistic risk assessment of fatigue crack growth and fracture incorporating NDE [15]. This work presents the development of probabilistic model components that represent a wide range of SHM system configurations and address the use of secondary inspections and SHM system degradation. Lastly, case studies are utilized to provide key insight into the potential benefits and pitfalls of SHM applications.

III. Hybrid NDE-SHM Life Management Approach

The addition of SHM models to the VNDE software was motivated by the obvious need for methodologies that can enable meaningful analyses of design tradeoffs for system life management strategies that involve both NDE and SHM technologies. A hybrid approach is proposed for fleet management considering selection / pairing of reliable SHM and NDE systems. Examples of possible maintenance approaches for a critical location include:

1. Fail-Safe Design [life prediction based on model only],
2. Scheduled NDE Maintenance [NDE],
3. Load Monitoring [SHM(1)],
4. Damage State Monitoring [SHM(2)],
5. Load Monitoring / Condition-Based Maintenance [SHM(1) + NDE],
6. Damage State Monitoring with Follow-up NDE Inspection [SHM(2) + NDE].

Considering the saying in engineering design that ‘you can’t have faster, cheaper and better – you can only have two out of the three’, for maintenance programs, there exists a similar compromise between aircraft availability, reliability and cost. Examples of such compromise are given as follows: (a) maximizing availability and total life of an aircraft may require higher costs for maintenance systems (such as SHM) or adversely impact reliability (b) minimizing cost of a maintenance program for a critical location may require limiting availability (such as reducing overall life) or sacrificing reliability, and (c) improving reliability may reduced availability due to longer depot maintenance periods or more costly SHM systems. An approach is needed to evaluate and compare the optimal tradeoffs between several maintenance approaches.

The VNDE software provides a rigorous quantitative approach to evaluate the benefits associated with NDE and SHM system applications. However, there is a need to summarize the rules-of-thumb as design criteria concerning when to apply NDE techniques and/or SHM systems for maintaining the quality over life for a critical location of interest. Ideally, an approach is needed that simply highlights the tradeoffs concerning availability, cost and reliability between methods. This would provide general insight on the best approach given the conditions of a critical location. In addition, from the perspective of NDE technique and SHM system design, there is a need to also highlight opportunities for technology research and development to address weakness of a particular method.

IV. Virtual NDE Tool for Probabilistic Risk Assessment and Cost Benefits Analysis

A. Integrated NDE and Economic Service Life Management Tools

A strategy for component life-cycle optimization incorporating NDE is presented first through the identification of the necessary components. These components are classified into two categories: refined system components, and performance measures. Refined system components are models, characteristics, and functions that are necessary for constructing the component life model. To achieve optimal component life management, the following refined system components must be well understood and integrated within a complete system approach: (1) identification of critical locations to inspect, failure analysis, and loss assessment, (2) initial quality and flaw initiation models (including material, geometry, and process models), (3) flaw growth models, (4) load and environmental monitoring, which evaluates the conditions under which the component will operate, (5) maintenance scheduling and repair tracking, (6) cost benefit analysis methodology, and (7) inspection technique capability, which is normally measured by probability of detection of a certain flaw type and size. Performance measures are used to evaluate how well a component or system behaves, and in the case of optimization applications they are usually formulated as objectives to be optimized and as problem constraints to be satisfied. The key life cycle performance measures are cost, mission capability (time in service), reliability, and delivery time or availability.

B. Probabilistic Life Management Model Incorporating NDE

Several prior approaches to probabilistic risk assessment for fatigue crack growth in aircraft structures were used as the foundation for the development effort. Two works in particular were used as the baseline for our effort: the work by Berens et al, at the University of Dayton Research Institute which resulted in the PROF (PRobability Of Fracture) software package [16], and the work by Kaczor at Bombardier Aerospace using the PRISM software package [17].

A key objective for this strategy is based on the ability to evaluate design parameters and cost benefits for a wide range of complex maintenance processes. One procedure that is prevalent in aircraft maintenance involves the repeated steps for resizing a part geometry to remove small cracks or corrosion. Figure 1 presents two examples where resizing repairs are applied in the field: (a) resizing an aircraft fastener site and (b) resurfacing an engine turbine component. Thus for example case (a), the incremental resizing and inspecting of holes using bolt hole eddy current (BHEC) inspection is performed until either the crack is no longer detected or the maximum hole size is reached, which requires the replacement of the entire panel section.

Two steps have been taken to address this objective with the proposed software framework. First, flexible model design through object-oriented building blocks is proposed. Second, a probabilistic analysis methodology is proposed to consider such maintenance procedures that incorporates a model for complex series of inspections and repairs. Figure 2 presents a flow diagram for a complex inspection and repair process model for a case study that tracks three separate part geometries (defined as states or features) and incorporates resizing repairs. According to this model, the three features correspond with three different hole sizes. Resizing is performed by removing material by a specified thickness *r*.

A probabilistic analysis methodology is utilized for evaluating the model component blocks ‘Inspect 1’ and ‘Repair 1 to 2’ found in Figure 2. $F_i^{(1)}$ and $f_i^{(1)}$ are defined as the cumulative density function (cdf) and probability density function (pdf) respectively, representing the flaw size distribution for feature type 1 (given by the superscript) at stage i (given by the subscript) in the inspect-repair sub-process. The subscripts *A*, *B*, *C*, and *R* are associated with flaw size distributions for the start of inspection, the portion associated with no call made (flaw not found), the portion associated with a call made (flaw detected), and the final repaired state after resizing respectively. $P^{(1)}$ is defined as the percentage of the probability density function called (flaws detected) by the inspection process for feature 1, and is given by

$$P^{(1)} = \int_0^\infty POD(a) f_A^{(1)}(a) da \, , \tag{1}$$

where *a* is associated with flaw size and *POD(a)* is the probability of detection function for the NDE inspection technique. The corresponding ‘no call’ and ‘called’ distributions resulting from the inspection are given by:

$$f_B^{(1)}(a) = (1 - POD(a)) * f_A^{(1)}(a) \, , \tag{2}$$

$$f_C^{(1)}(a) = POD(a) * f_A^{(1)}(a) \, . \tag{3}$$

For a resizing repair, $r^{(1)}$ is defined as a shift in flaw size of probability density function due to the repair process and corresponds to the amount in thickness of material removed by the repair. The pdf resulting from the repair is given by:

$$f_R^{(1)}(a) = f_C^{(1)}(a + r^{(1)}) = POD(a + r^{(1)}) * f_A^{(1)}(a + r^{(1)}) \, . \tag{4}$$

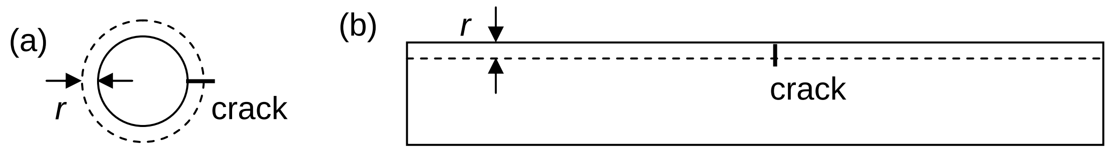

Figure 1. Examples of resizing repairs by removing material of thickness *r*: (a) resizing an aircraft fastener site and (b) resurfacing an engine turbine component.

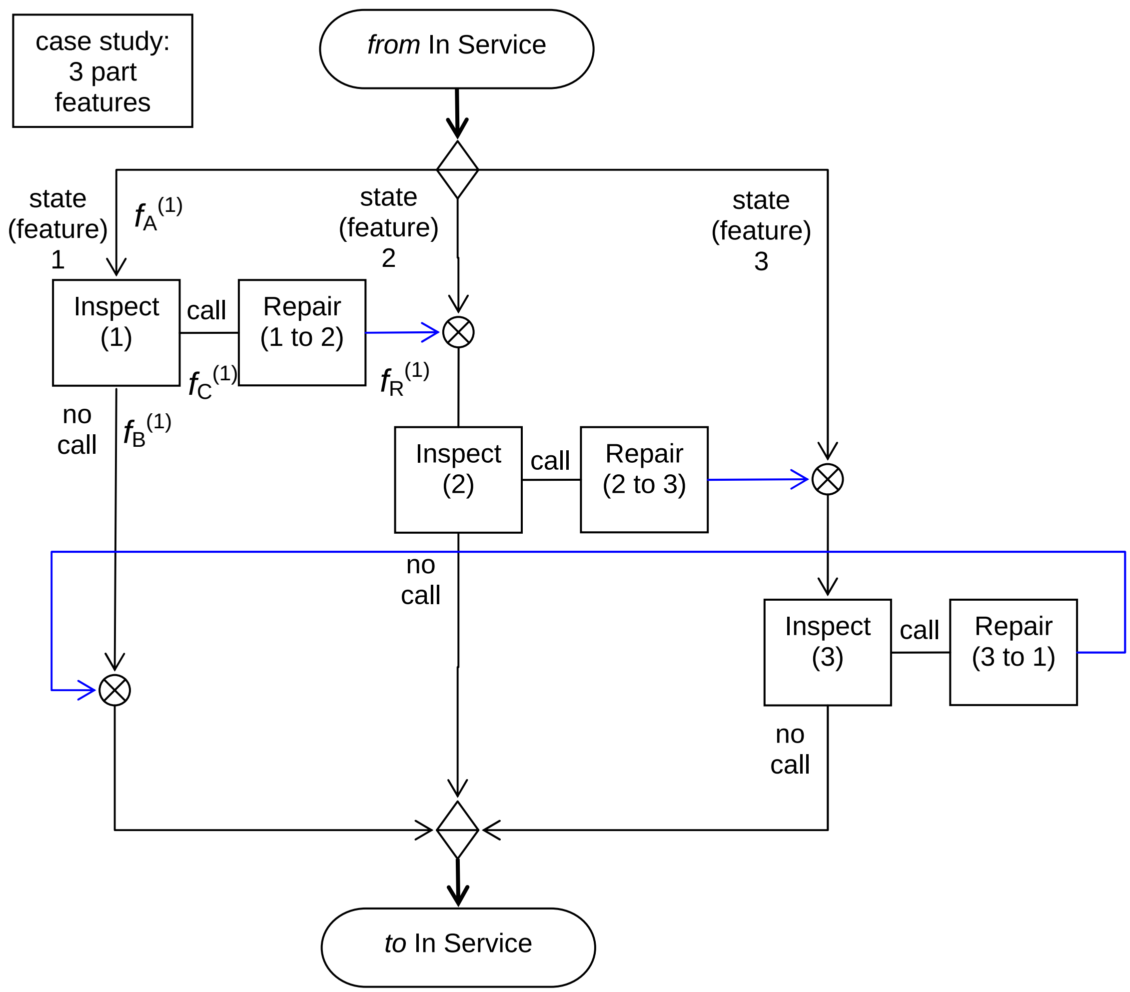

Figure 2. Flow diagram representing a complex series of inspection and repairs for a case study comprising three separate features and incorporating resizing repairs.

C. Software for Parametric Design Studies

Prior work has addressed development of a software platform to enable analysis of tradeoffs in NDE and SHM design in terms of product life cycle outcomes [14,18]. Several useful features have been incorporated in the software platform to facilitate specialized design studies. Any model factor can now be selected and defined as a variable for a parametric study. In particular, the inspection schedule can be varied both in length of time for each in-service period and number of total inspection intervals. Also, new visualization and tabular features have been included in the software to explore the design space in terms of key measures, e.g. total cost and maximum probability of failure.

D. Design Problem Space

The VNDE system when fully integrated with other important databases will provide the functionality to improve NDE design, structural health monitoring research and development, and condition-based maintenance programs. First, the VNDE platform provides the capability to address NDE design through improvements in NDE method selection for a given inspection problem, optimization of NDE sensors, hardware and scan plan, and optimization of automated signal classification algorithms based directly on performance measures. Research and development of structural health monitoring systems can also benefit from the VNDE system through design optimization of in-situ sensors and sensor layout, and exploration of the impact of sensor reliability (degradation) on model predictions. Lastly, condition-based maintenance and prognostics programs can also benefit by 1) indicating the best service life time window for application (i.e. limit prognostics decisions in early stages of life to eliminate false calls), 2) refining life prediction models based on monitoring the load and environmental conditions, 3) determining precise end-of-life date through and damage state awareness measurement data and 4) reducing model uncertainty (in life prediction and probability of detection models) over time.

V. Probabilistic Model for NDE-SHM Systems

A. Classes of Structural Health Monitoring Systems

Two classes of structural health monitoring systems are considered for representation in the software framework for integrated NDE design and product life management. The first approach is based on the acquisition of data for life prediction models. During in-service periods, distributed in-situ sensors can be used to measure the loading and environmental conditions experienced by the structure. Subsequently, these data can be used to improve fracture mechanics models to better predict the flaw state. This approach can be considered ‘indirect’, since the damage state in the future is estimated using a model prediction based on measurement input data. The most significant benefit of ‘indirect’ SHM schemes is a reduction in the uncertainty of the fracture mechanics models due to direct measurement of the loading and environmental conditions during in-service periods. As a preliminary approach to represent ‘indirect’ SHM systems within the analysis software, the capability to perform Monte Carlo simulations was provided to explore the sensitivity of performance measures such as cost and reliability with respect to SHM system parameter variability and uncertainty in the economic service life model.

The second approach is based on the acquisition of nondestructive evaluation data using in-situ sensors to quantify the damage state of a structure. This approach is classified as a ‘direct’ method, requiring that the damage state be observable in distributed sensor data. Two sub-classes of SHM damage characterization systems are defined as global health monitoring systems incorporating distributed sensors such as strain gauges and acoustic emission transducers, and local methods for critical structural locations using ultrasonic and eddy current sensors. In the next section, the theory and software implementation of a probabilistic model for ‘direct’ SHM systems will be presented.

B. Inspection Model for Structural Health Monitoring

A strategy is presented for incorporating SHM systems into a design platform for integrating various nondestructive inspection (NDI) design and product life management tools and for enabling analysis and optimization of design tradeoffs in terms of reliability, cost, fleet availability, and mission capability. A key objective for this work is to develop the capability to evaluate SHM design parameters and cost benefits addressing a wide range of potential SHM implementations. The approach adapts object-oriented building blocks, originally developed to represent maintenance programs incorporating NDI, for the case of SHM systems [14].

Figure 3 represents a diagram of a generic SHM process. First, there are two time intervals to consider: one associated with each opportunity for decision on maintenance (i) to be performed in the field, and an in-service SHM data acquisition time interval (j) at which an assessment of the damage state can be performed. It is important to distinguish between these two time intervals, since data may be acquired and a damage state estimate may be performed at a rate different than the rate corresponding to the opportunity for decisions on performing in-field maintenance (in the form of secondary inspections and/or repairs.) For each data acquisition time interval (j), data can be acquired from each sensor (k) in the array for a given number of samples (l). The number of samples (l) may be large for the case of acoustic emission measurements for impact damage or quite small for humidity sensors for corrosion monitoring. Starting with the raw data, signal processing and feature extraction algorithms are applied to filter and extract features as a set of scalar values (n). Signal classification can subsequently be applied to a database of feature vectors collected over time to estimate the damage state ($\hat{a}$) for each critical location (m). For each opportunity to assess the damage state and perform a maintenance action, a damage decision criterion is applied based on a maximum acceptable critical flaw size (a_{cr}). A database of damage state estimates ($\hat{a}$) for prior decision intervals and data acquisition periods (i,j) may be used in the decision process. The final step is the decision of whether or not to perform a maintenance action such as a secondary inspection or repair.

From the perspective of quantifying the reliability of a SHM system, there is an underlying relationship that must be evaluated between accuracy in the damage state estimate ($\hat{a}$) with respect to the actual damage state (a), with special interest placed on the critical flaw size (a_{cr}) that prompts a maintenance action. This probability of detection assessment is no different from the "$\hat{a}$ versus a" analysis procedure previously devised for NDE systems [19]. Although a model-based approach including each analysis step for the SHM process shown in Figure 3 would be ideal, it is proposed, as a first approximation, to represent the relationship between the flaw size and the probability of detection and false call rate directly using a four parameter probability of detection model:

$$POD(a,t) = \alpha + (\beta - \alpha)\left\{1 + \exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{\ln a - \mu}{\sigma}\right)\right]\right\}^{-1}. \tag{5}$$

where α corresponds to the false call rate and β is defined as 1 minus a random miss rate. Use of a four parameter POD model has been explored to address the observation that both hits and misses are often made for reasons that are independent of crack length [20].

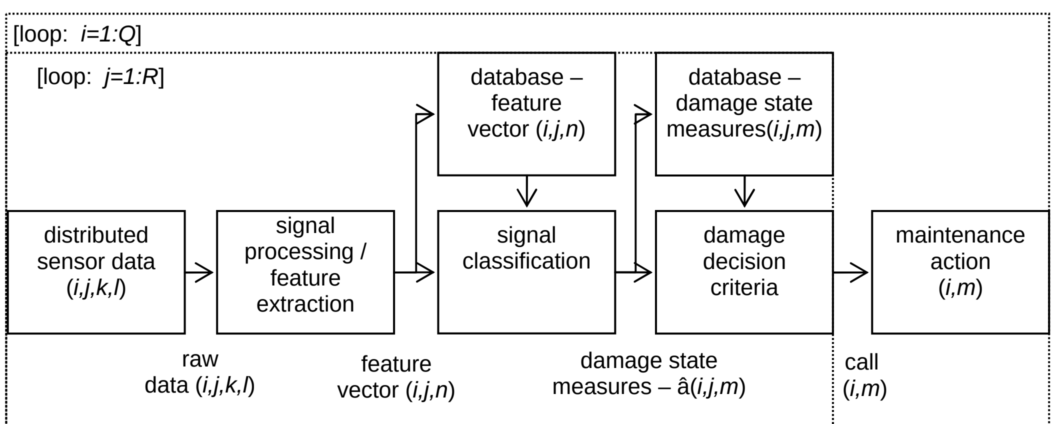

Figure 3. Flow diagram representing model of structural health monitoring system identifying the analysis steps from the sensor data to the decision on a maintenance action such as a secondary inspection or repair.

C. Probabilistic Model for Hybrid NDE-SHM System

Figure 4 presents a flow diagram for a basic SHM system integrated with an in-service period, with the opportunity for in-field maintenance incorporating a secondary inspection and repair process (with j = 1). A probabilistic analysis methodology is utilized for evaluating the model component blocks 'Inspect 1 - SHM', 'Inspect 2 - NDE' and 'Repair' found in Figure 4. In this formulation, $F_p^{(1)}$ and $f_p^{(1)}$ are defined as the cumulative density function (cdf) and probability density function (pdf) respectively, representing the flaw size distribution for feature type 1 (given by the superscript) at stage p (given by the subscript) in the inspect-repair sub-process. The subscripts A, B, and C are associated with flaw size distributions for the start of the SHM process, the portion associated with no call made (flaws not found), and the portion associated with a call made (flaws detected). $P_{SHM}^{(1)}$ is defined as the percentage of the pdf called (flaws detected) by the SHM process, and is given by

$$P_{SHM}{}^{(1)} = \int_0^\infty POD_{SHM}(a) f_A^{(1)}(a) da \,, \tag{6}$$

where a is associated with flaw size and $POD_{SHM}(a)$ is the probability of detection function for the SHM process. The corresponding 'no call' and 'called' distributions resulting from SHM are respectively given by

$$f_B^{(1)}(a) = (1 - POD_{SHM}(a)) * f_A^{(1)}(a) \,, \tag{7}$$

$$f_C^{(1)}(a) = POD_{SHM}(a) * f_A^{(1)}(a) \,. \tag{8}$$

A secondary inspection given in block 'Inspect 2 - NDE' can also be evaluated in a similar fashion, where $P_{NDE}^{(1)}$ is defined as the percentage of the pdf called (flaws detected) by the NDE procedure, and is given by

$$P_{NDE}{}^{(1)} = \int_0^\infty POD_{NDE}(a) f_C^{(1)}(a) da = \int_0^\infty POD_{NDE}(a) POD_{SHM}(a) * f_A^{(1)}(a) da \,. \tag{9}$$

The corresponding 'no call' and 'called' distributions resulting from the secondary NDE procedure are respectively given by

$$f_D^{(1)}(a) = (1 - POD_{NDE}(a)) * f_C^{(1)}(a) = (1 - POD_{NDE}(a)) POD_{SHM}(a) * f_A^{(1)}(a) \,, \tag{10}$$

$$f_E^{(1)}(a) = POD_{NDE}(a) * f_C^{(1)}(a) = POD_{NDE}(a) POD_{SHM}(a) * f_A^{(1)}(a) \,. \tag{11}$$

For this example, the resulting repair distribution represents a return to the original state of the part for those flaws called both by the SHM process and the NDE technique, and can be expressed as

$$f_R^{(1)}(a) = P_{NDE}{}^{(1)} \cdot f_{R\_EIFS}^{(1)}(a) \,, \tag{12}$$

where $f_{R\_EIFS}(a)$ represents the equivalent initial flaw size pdf for the original part. This process is repeated for N iterations corresponding to each SHM manager decision and maintenance opportunity (i). Following this process, depot maintenance or end of life may be reached depending on the design life of the aircraft.

Two variations to this generic SHM model are proposed. Figure 5 presents a flow diagram representing a model of in-service period with SHM and an in-field maintenance process including an option to remove from service. This model variation provides the opportunity to evaluate the case where flaws detected lead to the associated aircraft being removed from service. Another important issue concerns the degradation of the SHM system over time. This can be modeled by defining the probability of detection function in terms of parameters that vary with time, as

$$POD(a,t)=\alpha(t)+\left(\beta(t)-\alpha(t)\right)\left\{1+\exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{\ln a-\mu(t)}{\sigma(t)}\right)\right]\right\}^{-1}. \tag{13}$$

Figure 6 presents a plot of a POD function that varies with time, representing potential degradation of the SHM process through changes in the 50% detectable flaw size and the random missed flaw rate.

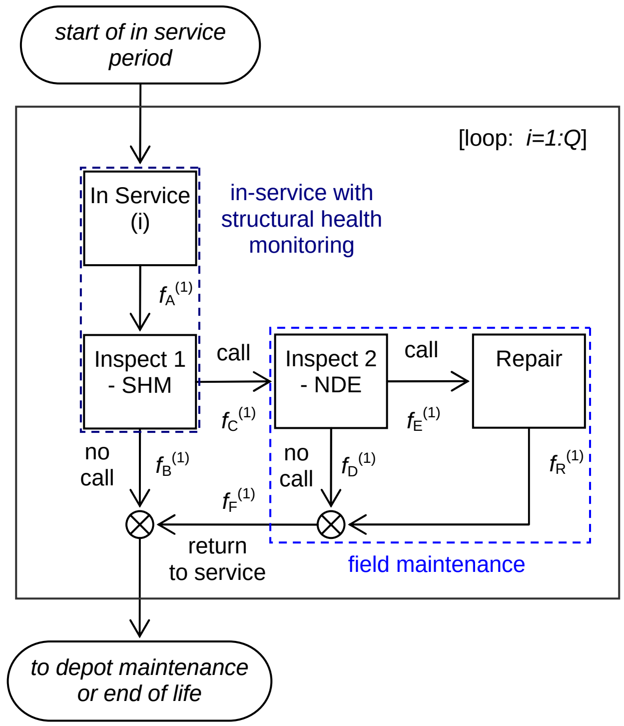

Figure 4. Flow diagram representing model of in-service period with structural health monitoring and optional in-field maintenance.

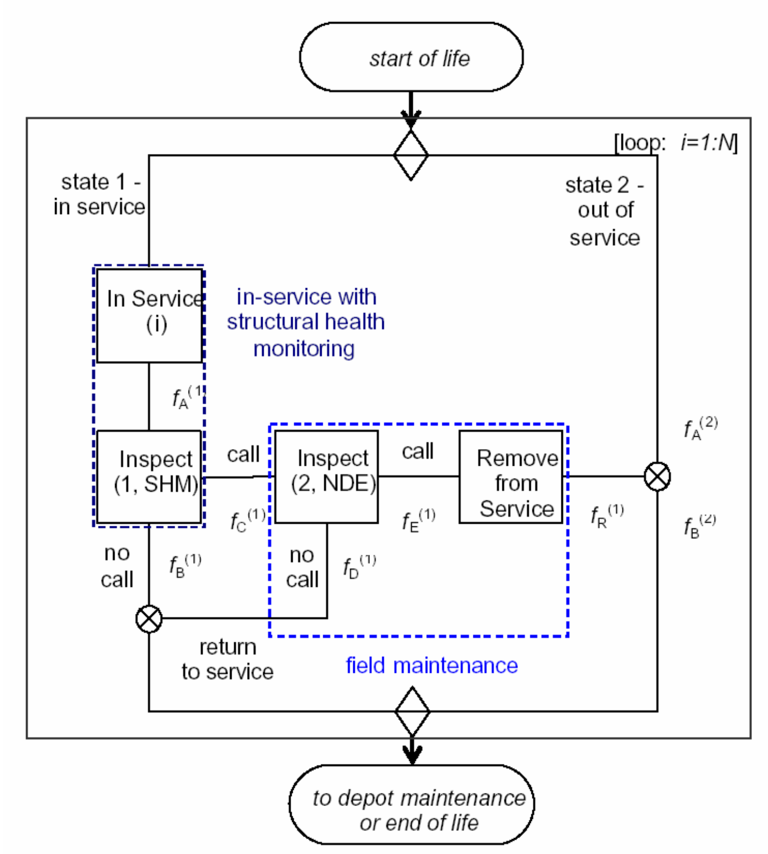

Figure 5. Flow diagram representing model of in service period with structural health monitoring and in-field maintenance including option to remove from service.

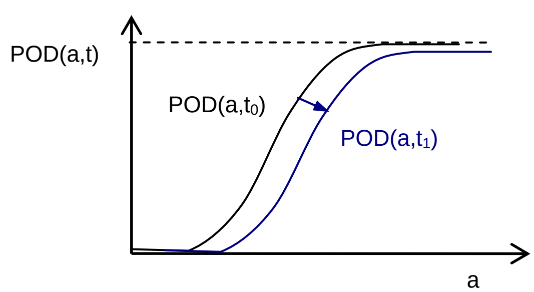

Figure 6. Probability of detection (POD) function with variability in model parameters over time.

VI. Case Studies

A. NDI Reliability Parametric Study

A full factorial parametric study was performed varying each of the parameters in the four parameter POD model between two levels: a baseline and a degraded performance level (Table 1). The hypothetical maintenance case study was designed including three in-service intervals with two inspection events. The POD model was held constant for the two inspections. The probability of failure (POF) model included both probability of fracture and probability of a crack growing to critical. The critical flaw size was 0.75". The results from the parametric study are displayed as a function of total life-cycle cost and maximum probability of failure in Figure 2. Each of the sixteen results are identified by labels that indicate the factor level varying between baseline (0) and degraded (1) conditions for each of the four parameters (a50,σ,FC,RMC). Trends for each parameter are also presented using vectors in the plot. Degraded performance in terms of increased median detected crack lengths by 0.010" (*associated with level of procedure experience of the operator*) was found to result in a higher POF and lower total cost. A reduction in the skewness or slope of the POD curve (*associated with differences in skill and experience*) resulted in only very small increases in both POF and total cost. An increase of 1% in the false call rate (*associated with degraded concentration and over-sensitivity to noise*) was found to increase total cost with little impact on POF. Lastly, an increase in the percentage of random missed calls by 10% (*associated with a lack of integrity, poor focus, or a bias concerning the expected frequency of detected cracks*) was found to significantly increase the probability of failure with a slight decrease in total cost.

Although the random missed call rate was found to significantly impact the probability of failure, the degree of sensitivity was found to be less than expected. There are several reasons for the probability of failure results not being more significant for an increase in the random missed flaw rate from 0% to 10%. The first source concerns the nature of the POF calculation. Although consisting of both probability of fracture and probability of a crack growing to critical, the POF function is often dominated by the probability of fracture component. Since probability of fracture is dependent upon the relation between stress intensity factor and crack size, which is quite sensitive to changes in flaw distribution for very small crack lengths but less for cracks in the mid-range, the function is generally less sensitive to changes in the random missed call rate (RMC) and more to the median detectable flaw size (a50). If the probability of failure calculation was solely dependent upon a crack growing to the critical flaw size, changes to the random missed call rate would affect the POF much more significantly with respect to similar changes in the median detectable flaw size. Second, multiple inspection opportunities also significantly reduce the probability of a missed flaw. In particular, if inspections are independent and intervals between inspections are short, multiple inspections can be used to mitigate poor inspection performance. Finally, these observed changes should not be considered to be absolute trends, but are dependent on the equivalent initial flaw size distribution, flaw growth model, and interval of inspection. Through these simulated studies, unexpected insight was achieved concerning the influence of the POD parameters on cost and reliability.

Table 1. Baseline and degraded performance levels for parametric study.

Parameter	Baseline Level (0)	Degraded Level (1)	Units
a50	0.060	0.070	(in.)
σ (skewness)	0.02	0.2	()
FC	0.0	1.0	(%)
RMC	0.0	10.0	(%)

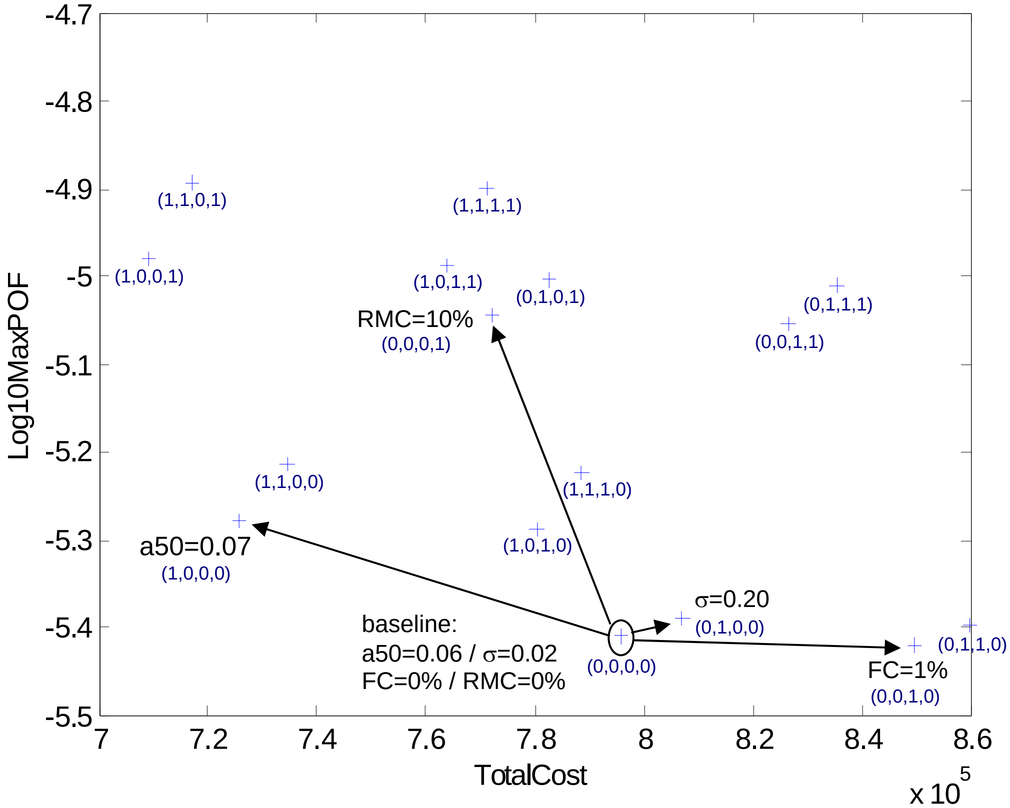

Figure 7. Plot of total cost versus probability of failure for varying the four POD model parameters (a50,σ,FC,RMC) between two levels, highlighting the main trends with respect to the baseline case (0,0,0,0).

B. NDE-SHM Cases Studies

Several case studies are presented to both demonstrate the capability of the software platform and gain a better understanding of the dynamics of the SHM system model. The first study explores the effect of varying the frequency of SHM calls for a fixed total service life. This hypothetical study only includes variable costs associated with structural health monitoring calls and repairs. Figure 8 shows the simulated results for probability of failure and cumulative maintenance cost as a function of time and number of SHM cycles. For this study, a higher frequency of SHM calls will result in higher life-cycle cost. The source of this higher cost is twofold. First, the total cost associated with labor hours for data interpretation is increased with the frequency of SHM calls. In theory, this cost could be quite small if robust automated algorithms for data interpretation are used. In practice, given the high cost for repairs and potential for false calls due to unknown conditions not considered in the original design, secondary assessments of the SHM data by an expert inspector are often necessary. The second source for higher costs occurs over the later part of the in-service period, where non-critical flaws are called by the SHM system. Ideally, minimizing the frequency of calls while maintaining an acceptable level of reliability in terms of probability of failure is a fundamental design principle for minimizing life-cycle costs. Alternatively, higher frequency rates of SHM calls can significantly improve reliability. This strategy is particularly valuable when the SHM system is designed to only detect very large flaws, the crack growth model is nonlinear, or uncertainty is present in the crack growth model parameters.

A second case study explores variations in the detectable flaw size for both an SHM system (Inspection 1 – SHM) and a secondary NDE inspection technique (Inspect 2 – NDE). Specifically, the 50% detectable flaw size parameters for the SHM and NDE inspection models were both varied from 0.02" to 0.10" as a full-factorial study. Figure 9 presents the design solution space resulting from the study in terms of maximum probability of failure and total cost. This design solution space plot provides the means to select the Pareto solutions providing the optimal tradeoff between the two objectives. Furthermore, it is possible to select from this reduced solution set a design that minimizes cost while maintaining an acceptable probabilty of failure, typically set at 10^{-6}. Using these criteria, the optimal SHM system 50% detectable flaw size was found to be 0.06", with the secondary NDE system 50% detectable flaw size set to any value greater than 0.05".

A third case study explores the sensitivity of cost and reliability measures to SHM system false call rate. Due to space limitations, only a discussion of the trends in the results is presented. As previously mentioned, the issue of false calls can hinder the application of SHM systems. Given the challenging problem of reliably detecting cracks using distributed sensors, false calls rates are expected to be comparable or higher with respect to NDE cases, typically on the order of 1%. However, although a 1% false call rate may be acceptable for less frequent NDE inspections, when SHM calls are made at a more frequent rate, a greater number of locations will be falsely called over the life of the aircraft and thus prompt some form of secondary maintenance action. This is especially problematic given that the model predicts that most calls that are initially made are most likely false calls, thus having a negative impact on the product life management program and its sponsors. Secondary inspections were found to be quite beneficial in mitigating cost by limiting unnecessary repairs due to false calls. However, if the cost of secondary inspections is not small, the total cost may be excessive and thus hinder practical use.

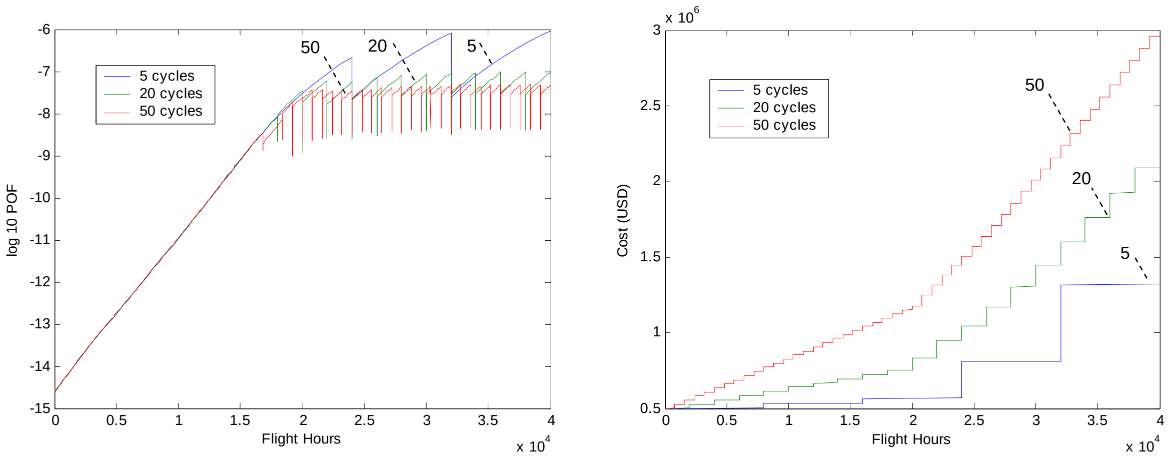

Figure 8. Plots of (a) probability of failure and (b) cumulative maintenance cost as a function of time and SHM cycle number.

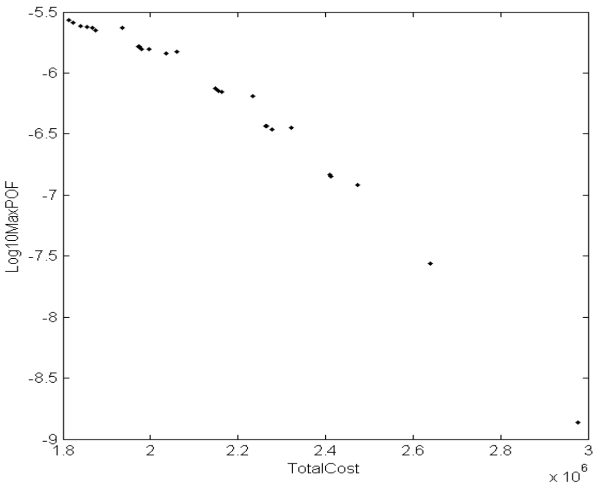

Figure 9. Design solution space for varying SHM and secondary NDE sensitivity in terms of maximum probability of failure and total cost.

C. Investigating Impact of SHM System Degradation

A final case study explores the impact of degradation in SHM system performance over time. The total service life was divided into ten service periods separated by nine maintenance events consisting of SHM data processing and subsequent field inspection and repair. A variable probability of detection was assigned to the SHM system as follows: maintenance events 1 – 5 were assigned the SHM POD labeled t_0 in Figure 10(a), t_1 was assigned to the SHM system at maintenance event 6, t_2 to maintenance event 7, and t_3 to maintenance events 8 and 9. Figure 10(b) compares the probability of failure history for the time varying SHM POD case just described to that of a case where the POD of the SHM system is fixed to that labeled t_0 in Figure 10(a). Figure 10(b) shows that the variable POD case results in an undesirable increase in probability of failure. If such a condition is experienced in the field, replacement of the sensors to maintain inspection reliability is suggested. Not shown here is the fact that the total cost for the variable POD case is lower than that of the fixed POD case, because finding and repairing less flaws results in lower costs at the expense of a higher risk of failure. However, if degraded performance leads to increased false calls, the model indicates that much of the earliest calls will be either false or premature calls of very small cracks. Procedures must be in place to manage the occurrence of such false calls early in the implementation of SHM systems through secondary expert review of data and inexpensive follow-up inspections to mitigate unexpected costs and issues concerning trust in the system with the aircraft maintainer.

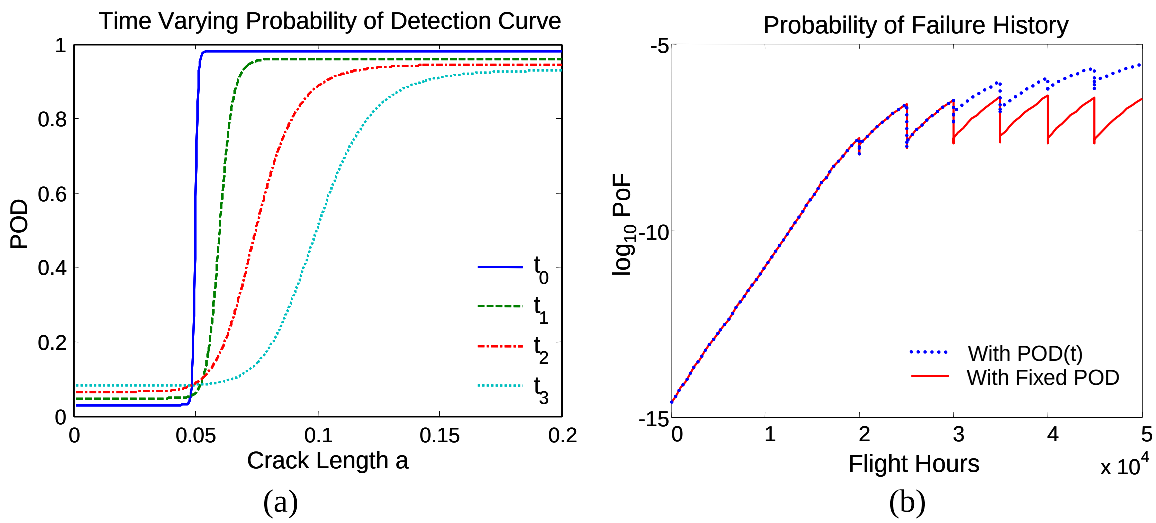

Figure 10. Effects of SHM system deterioration: (a) time varying POD, (b) resulting POF.

VII. Conclusions and Recommendations

Hybrid life management strategies for new and aging aircraft have been proposed that combine traditional non-destructive evaluation (NDE) methods and recently developed structural health monitoring (SHM) technologies. To best address the management of the vast array of critical structural locations over the service life of an aircraft fleet, a 'hybrid approach' to fleet management is encouraged considering a case-by-case evaluation of the most appropriate maintenance approach: 1) fail-safe design (no inspection), 2) scheduled nondestructive inspection, 3) loading condition monitoring, 4) damage state monitoring, 5) load condition monitoring with condition-based maintenance, and 6) damage state monitoring with secondary nondestructive inspection.

A software package was presented for integrating NDE and SHM design with product life management models. Based on probabilistic models of fatigue crack growth, NDE detection capability, repair, probability of failure, and cost, the demonstration cases show the ability of the software tool to assess the effects that changes in SHM parameters, NDE parameters, and maintenance scheduling can have on time-dependent reliability and economic service life objectives. Furthermore, the ability of the software to facilitate design tradeoff assessment and optimization was demonstrated for goals such as cost, reliability, and system availability.

Future work will explore the sensitivity of model trends to cost parameter levels, and acquire better data on flaw size distributions and real costs (of repairs) for promising applications. Long term efforts plan to explore the development of numerical and empirical models to better represent variations in human factors in NDE models and sensor degradation in SHM models. Probabilistic models will be studied to address the assumption of statistical independence for multiple measurements of the same component or inspection system over time.

Lastly, data for several VNDE model components such as equivalent initial flaw size distribution and flaw growth history data have been found to be difficult to obtain. Although some assumptions are necessary for most engineering and economic assessments, fundamental steps are also needed to improve the quality of available model data. Collaboration throughout the aerospace community is needed to make available any existing data and facilitate the acquisition of such data where needed. Laboratory studies, aircraft teardown studies, the application of quantitative NDE techniques for flaw characterization, in situ sensors for damage state, loading and environment condition tracking, numerical models, and well managed databases are all integral to build the necessary data sets. Continued work to build relationships with other members of the community to support and acquire this data is also needed.

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